An OSSE framework for SMAP Level 4 soil moisture assimilation products

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Motivation and Objective

Satellite measurements (retrievals) of surface soil moisture from the Soil Moisture Active Passive (SMAP) mission are subject to errors and cannot by themselves provide the space-time coverage that is often needed (for example, in forecast initialization applications). A land data assimilation system can merge the SMAP soil moisture retrievals with information from land surface models and antecedent meteorological data, information that is spatio-temporally complete but likewise uncertain. This merger yields the suite of **SMAP Level 4 data assimilation products** (including root zone soil moisture and evapotranspiration).

For the design of the SMAP mission it is critical to understand just how uncertain the surface soil moisture retrievals can be while still achieving the science objectives of the mission. Here, we present an Observing System Simulation Experiment (OSSE) that determines the **contribution of surface soil moisture retrievals to the skill of land data assimilation products as a function of retrieval and land model skill** (Reichle et al., 2008a).

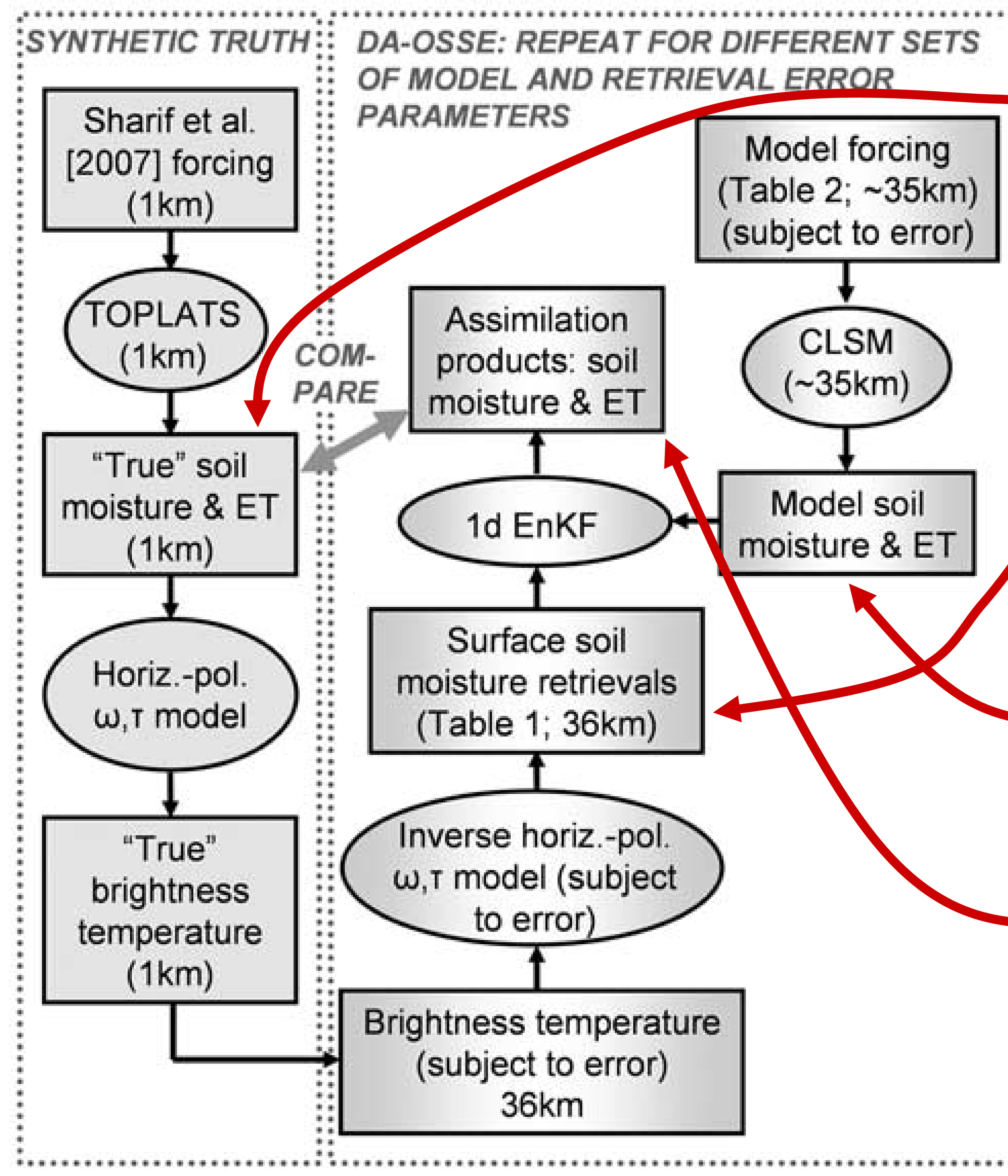


Figure 1: Flow diagram of the OSSE.

Approach: Fraternal Twin Experiment

1. Truth: "True" soil moisture fields and passive microwave brightness temperatures (L-band) are from a high-resolution (1 km) long-term (1981-2000) integration of the TOPLATS land surface model over the Red-Arkansas river basin, using high-quality meteorological forcing.

2. Observations: From the "true" brightness temperature fields, we simulate **N_R=12 different retrieval soil moisture data sets** at a typical satellite footprint scale (36 km) and temporal resolution (at most once a day). The retrieval data sets reflect various sources of uncertainty with different error structure and magnitude.

3. Land surface model: We use the NASA Catchment land surface model and construct **N_M=8 distinct modeling scenarios** with different levels of errors in model parameters and forcing data.

4. Scaling and data assimilation: Each retrieval data set is scaled to the soil moisture climatology of each model scenario for bias removal and then assimilated into each model scenario with an adaptive Ensemble Kalman filter (EnKF) for a total of **N_R*N_M=96 assimilation experiments**. The assimilation products are compared against the assumed "truth" to determine the error levels for contouring.

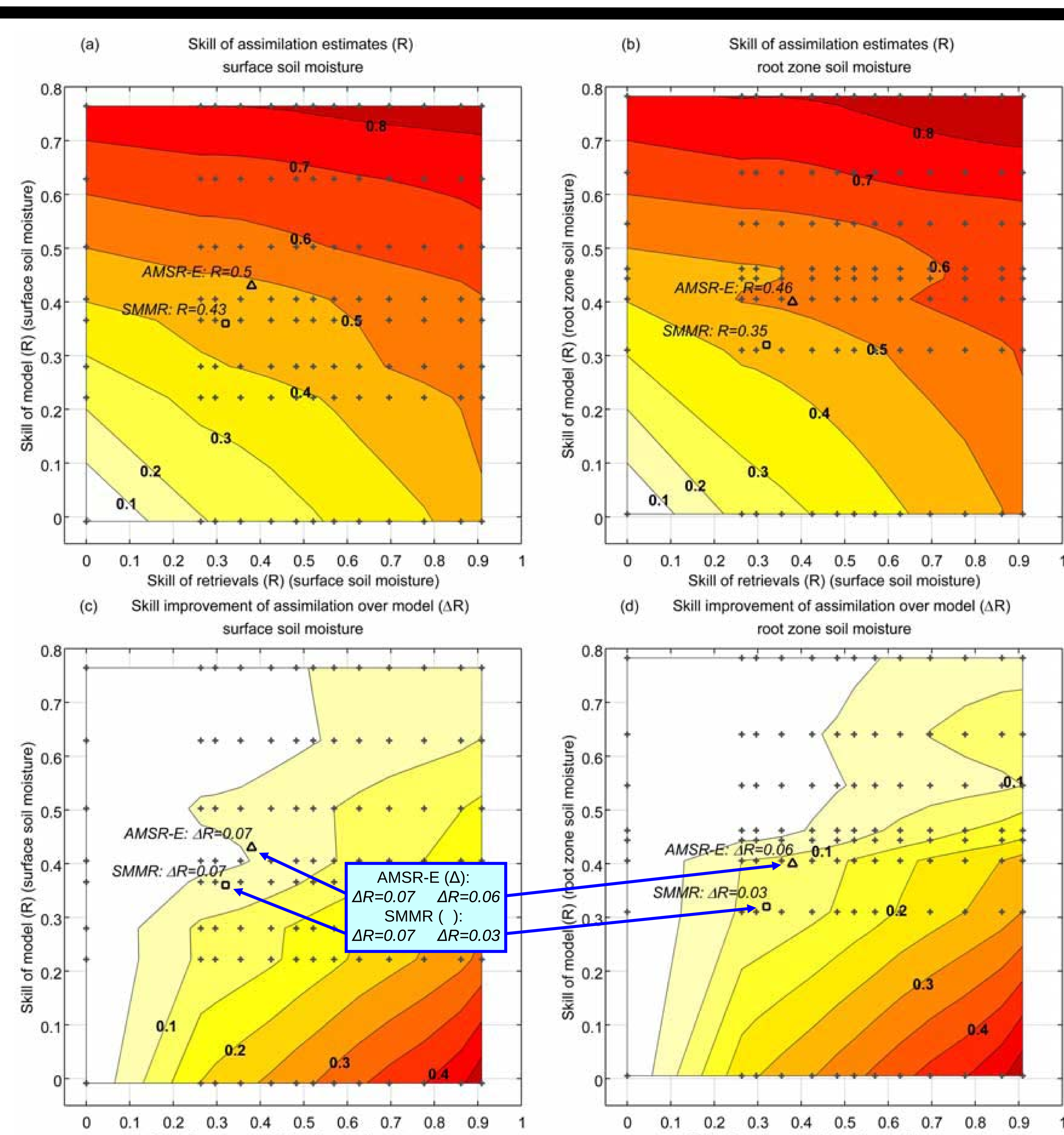
Figure 2:

(a, b) Skill (R) and (c, d) skill improvement (ΔR) of assimilation product for surface (a, c) and (b, d) root zone soil moisture as a function of the (ordinate) model and (abscissa) retrieval skill.

Skill is measured in terms of R (=anomaly time series correlation coefficient against truth). Skill improvement is defined as skill of assimilation product minus skill of model estimates.

Each plus sign indicates the result of one 19-year assimilation integration over the entire Red-Arkansas domain.

Also shown are results from Reichle et al. (2007) for (triangle) AMSR-E and (square) SMMR.



Model Error Calibration

Each assimilation experiment must achieve near-optimal performance – otherwise the information contributed by the retrievals cannot be compared across experiments.

Performance depends on model and observation error parameters and can be diagnosed by the skill of the assimilation estimates (vs. truth) and by the variance of the normalized innovations. We use an adaptive EnKF (Reichle et al., 2008b) to ensure that each assimilation experiment achieves near-optimal performance.

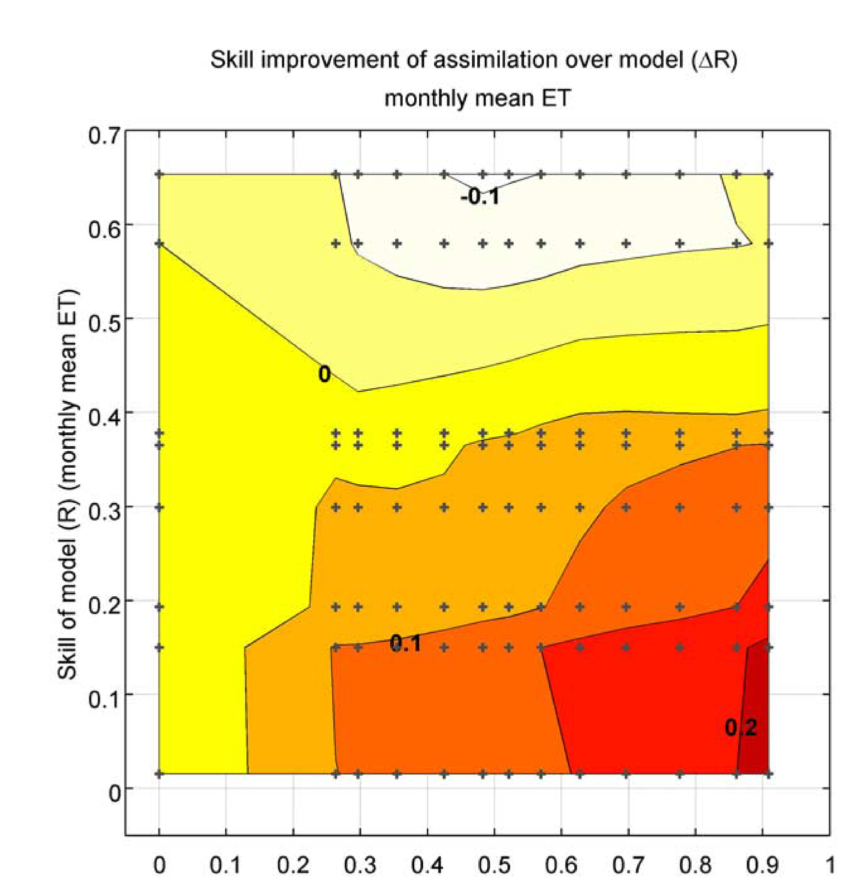


Figure 3: Skill improvement for monthly mean ET assimilation product. Abscissa, ordinate, and plus signs as in Figure 2.

Results

The skill of the assimilation products generally increases with the skill of the model (Figure 2a, b).

The skill of the assimilation products is more sensitive to model skill than to retrieval skill.

Assimilation of soil moisture retrievals adds skill (relative to model product)*.

The improvements in R through assimilation increase with increasing retrieval skill.

Even retrieval data sets of poor quality contribute some information to the assimilation product, particularly if model skill is modest.

The OSSE results are consistent with numbers obtained from assimilation of AMSR-E and SMMR retrievals and validation against in-situ measurements.

*Note: The skill of the assimilation estimates does not necessarily exceed the skill of the retrievals because:

1. the assimilation system does not optimize R itself,
2. nonlinearities pervade the system,
3. the selection of model error parameters and the scaling algorithm are imperfect,
4. differences exist in the layer depths for the assumed "truth" and the Catchment model,
5. the data are averaged to daily values, and
6. the ensemble size (N_ens=12) used in the EnKF is small.

Future Directions

Further improve model error calibration technique (through additional adaptive tuning).

Add more model scenarios to refine contour plots.

Include retrievals based on active (radar) measurements.

References

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